Hindawi
Journal of Advanced Transportation
Volume 2023, Article ID 9283130, 13 pages
https://doi.org/10.1155/2023/9283130

WILEY | Hindawi

Research Article

An Optimization Model for Structuring a Car-Sharing Fleet Considering Traffic Congestion Intensity

Parisa Ahani,[1] **Amilcar Arantes**,[2] **and Sandra Melo**[3]

[1]CERIS, MIT Portugal Program, Sustainable Energy Systems, Instituto Superior Tecnico, Universidade de Lisboa, Lisbon, Portugal
[2]CERIS, Instituto Superior Tecnico, Universidade de Lisboa, Lisbon, Portugal
[3]CEiiA, Center of Engineering and Development, Matosinhos, Portugal

Correspondence should be addressed to Parisa Ahani; prsahani1@gmail.com

Received 18 April 2022; Revised 18 September 2022; Accepted 24 November 2022; Published 6 February 2023

Academic Editor: Mohammad Miralinaghi

Ever-growing mobility and traffic congestion within urban areas make the need for a sustainable form of transport inevitable. Traffic congestion has a significant effect on the amount of energy consumption of a vehicle and, as a result, on its associated environmental impacts. Any decision-making regarding structuring a fleet without taking into account the traffic congestion level (TCL) will lead to a less sustainable fleet with higher environmental and economic costs. To address this issue, this study examines the effects of the traffic congestion intensity level on the fleet structure of an urban car-sharing company over a certain planning period. We present a new optimization framework for finding an optimal vehicle composition of the fleet of an urban car-sharing company considering the energy consumption of vehicles at different traffic congestion levels. The results show that electric vehicles (EVs) are more competitive than diesel vehicles (DVs) in high-peak traffic congestion from the outset of the planning period. In addition, we perform a sensitivity analysis to take into account the effects of specific uncertain parameters such as the energy and purchasing costs of EVs on the total cost of ownership. As expected, the purchasing price of EVs, energy prices of DVs, and increase in diesel prices have the highest impact on the total cost.

1. Introduction

The idea of several people sharing the same car can be traced back several decades ago [1]. Car-sharing is a type of shared mobility that offers renting cars on a needed basis for as little as 10 minutes [2] and often by the hour when other modes of transport are not available or are not suitable [3]. The users can be passengers, companies, and public agencies [4]. The station of car-sharing is usually close to the location of transportation modes, and the payment is based on travel distance or time spent [4].

Car-sharing has the potential to reduce vehicle use, ownership, and delays in car purchases [5–7]. It is seen as a solution to address the issues of congestion, pollutants, and the occupancy rate of vehicles within urban areas [8, 9]. This leads to increasing urban sustainability from environmental, economic, and societal points of view worldwide. [10–13]. Chen and Kockelman [14] estimated a reduction of 51% in energy consumption and greenhouse gas (GHG) emissions for what they have defined as a "good candidate for shared mobility."

In two studies [10, 11], the authors conducted a survey of members of a car-sharing club in the US, looking specifically at the impacts of car-sharing on household vehicle ownership. The results showed that the rate of vehicle ownership among club members decreased from 0.47 to 0.24 vehicles per household. In the last decade, the car-sharing market in Europe has expanded, and in Germany, as the largest car-sharing market in Europe, an increase in user usage from 0.26 million in 2012 to 1.29 million in 2020 was reported by Roblek et al. [15].

Various research studies have shown that the demand for car-sharing as a means of mobility in any form is increasing worldwide [16–19]. In many countries around the world, car-sharing or short-term auto access [20] is known as a system to minimize ownership transportation costs and the negative effects of car use. The car-sharing industry has recently significantly increased its market [21, 22]. In the past decade, advancements in communication technologies and smartphone applications have led to the emergence of car-sharing companies such as DriveNow and Car2Go. Autolib in Paris is one of the known operators in car-sharing systems that offers electric car-sharing services with at least 1750 electric vehicles (EVs) and 65,000 members. Such companies own a number of vehicles and deal with any cost related to the operation of their fleet in the car-sharing service.

There is a trend toward the use of electric vehicles such as gasoline-electric hybrids and electric vehicles in car-sharing systems [20, 23]. EVs, in comparison to their conventional counterparts, have lower operational and maintenance costs, and their zero tailpipe emissions are another option for operation in car-sharing services since they usually operate in urban environments. Furthermore, with regard to energy consumption, their performance at lower speeds is better than that of internal combustion engine vehicles (ICEVs) [24], which is an additional advantage during peak-hour traffic. The purchase price of EVs has thus far been the main barrier to their wider use. However, with increasing technological advancement, the cost of EV batteries, which makes up a large portion of the price of an EV, has been on a downward trend in recent years. Following Nykvist et al. [25]; the battery price decreased by 77% from 2007 to 2018, reaching an average cost of $230 per kWh. Thus, this downward trend in battery prices will lead to a reduction in EV purchase prices over time. In contrast, ICEVs have lower purchase prices. However, the fuel cost of an ICEV, which is the major cost during the lifetime of such a vehicle, is very unpredictable. The steep increase in oil prices and their wild fluctuations in recent years have affected the fuel cost of ICEVs. Accordingly, any decision for vehicle replacement based merely on the actual total cost of ownership of a vehicle without taking into account the concerned uncertainties might increase the cost in the long term.

To the best of our knowledge, no research study has been conducted on an optimal fleet replacement for a car-sharing service considering traffic congestion levels. This study introduces a new optimization framework to assist a car-sharing company in selecting the best investment strategy for structuring its fleet from different types of vehicle technology (EVs vs. ICEVs in particular) over a certain planning time period. The novelty of the developed framework lies in considering different traffic congestion intensity levels and various demand levels for a car-sharing service throughout a typical day of operation. The optimization framework will provide the operator with the best fleet composition for its car-sharing company over a certain planning period.

The remainder of the paper is organized as follows: Section 2 contains a literature review, and Section 3 describes the model and the optimization framework. In Section 4, the data and assumptions are presented, and Section 5 is dedicated to the results and discussion. The paper ends in Section 6 with the enunciation of some conclusions.

2. Literature Review

Various research studies have focused on fleet optimization for shared mobility systems [26–31]. In a study by Wallar et al. [28], the authors provided a model for optimizing fleet composition to distributions of vehicles for shared mobility service. They proposed an algorithm for determining the required number of vehicles, where they should be located at the start point, and how they should be routed to satisfy all travel demands in a particular period of time while enabling many passengers to be served by the same vehicle. Based on an analysis of historical taxi data from Manhattan in New York City, they presented a model estimating the number of required passenger cars to meet all daily taxi demands, with an average waiting time and an extra travel delay. Monteiro et al. [26] provided a model to optimize the fleet size by maximizing the number of served clients to satisfy the demand while minimizing the high number of parked vehicles in the station using a mixed-integer linear program. Nair and Miller-Hooks [29] presented an optimization model for fleet management of shared-vehicle services by using a stochastic mixed-integer program with joint chance constraints and random demand across stations to minimize cost car redistribution in a fleet.

Some research studies developed optimization models for electric mobility in car-sharing systems [32–36]. In another study by [32], the authors performed an extensive review of recent literature on car-sharing. They developed an optimization framework for the fleet composition of station-based car-sharing systems with heterogeneous fleets by considering three different types of vehicles: ICEVs, plug-in hybrid electric vehicles (PHEVs), and EVs. They demonstrated that existing infrastructure and well-established technology help ICEV growth and make PHEVs the best alternative compared to the other two types of vehicles. They concluded that EVs remain the best alternative considering environmental and global emissions and local pollutants, especially over long-term periods. In a research study by Bubeck et al. [34]; the authors analyzed the total ownership cost of electric mobility by considering the CO_2 subsidies offered to EVs and buyer premiums as an incentive on the German road up to 2050. The results showed that full and mild hybrid electric vehicles are currently more economical even without government subsidies. Moreover, they showed that buyer premiums are necessary to make EVs competitive in terms of cost, and from 2030 onward, EVs can survive as an economical option.

Although there have been various research studies focusing on fleet optimization in shared mobility and car-sharing systems, to the best of our knowledge, no research study has addressed optimizing car-sharing fleet structure considering the effect of traffic congestion. In this study, motivated by research studies on the fleet replacement problem in Urban Freight Transport (UFT) (see [37, 38], and [39], we introduce a novel optimization framework to assist a car-sharing company in choosing the best investment strategy for having different types of vehicles (in particular EVs vs. ICEVs) in its fleet over some planning time period. Despite some similarities between vehicle replacement in urban freight and car-sharing, there are differences between these two types of problems, which each deserve their own analysis. This work focuses on vehicle composition for car-sharing companies, whereas the focus of previous research studies has been on vehicle composition for UFT. The nature of the demand for urban freight transport throughout the day is different from that of car-sharing services. There are limitations regarding the operation of freight vehicles within a city during the day (in particular, during peak hours). However, there are no such restrictions in regard to passenger vehicle operations within urban areas. More importantly, the developed optimization framework takes into account the magnitude of traffic congestion, which is a novel approach even within the context of UFT.

3. Research Methodology

The aim of this research is to determine the best combination of different types of passenger vehicles for the fleet of a car-sharing company over a certain planning period. There are various vehicles of different types that can be used by a company to run its car-sharing service. Each vehicle has its own characteristics, which affect the associated costs. These costs include the purchase price, energy costs, operation and maintenance costs, and emission costs, to name the most important ones. In addition, depreciation rates for vehicles vary greatly, and accordingly, the corresponding salvage revenues are of various magnitudes.

Energy consumption is one of the main costs associated with a vehicle during its lifetime. Speed is a principal factor affecting the energy consumption of a vehicle and, as a result, the amount of emissions that the vehicle produces. Following He et al. [40], the optimal fuel consumption occurs in the speed range of 45–80 km/h, whereas EVs have lower energy consumption in the range of speeds between 20 km/h and 40 km/h [41]. On the other hand, during peak hours, traffic congestion affects the speed of a vehicle. In congested areas, vehicles are faced with frequent stopping and going and operating in lower-level gears, which makes them consume more energy. Therefore, the developed optimization framework considers these important factors by dividing a typical day of operation into several blocks of time depending on the traffic congestion level of that day. The idea of dividing a typical day of the planning time period into several blocks of time was motivated by previous research studies on electricity supply planning Huang and Wu [42] and Wu and Huang [43]. To demonstrate the idea of dividing a typical day of operation into different blocks of time, we use the data regarding the average speed given during 22 hours of a day in Ji et al. [44], where the authors presented the average speed of 20,000 taxi datasets recorded by GPS in part of the city of Shenzhen in China for 22 hours from 1 AM to 11 PM on a weekday. An average speed of less than 30 km/h can be demonstrated more than 70% of the time, with the sharpest decline in average speed occurring during the peak hours of 6–8 AM and 4–6 PM.

Thus, based on the average speed given there and the amount of consumption for the corresponding velocity given by He et al. [40] and Grée et al. [41]; we illustrate in Figure 1 how a typical day of operation is divided into three blocks of low, medium, and high congestion levels.

The developed optimization framework will determine a more sustainable car-sharing fleet structure for the company over a certain planning period while satisfying the interests of the concerned stakeholders. In addition, uncertainties related to various parameters such as energy, purchase, emission, and maintenance costs need to be addressed. These uncertainties have an impact on the total cost of running a car-sharing service, and any decisions regarding the composition of the fleet taken without considering these can result in extra costs for the company. Accordingly, we perform a sensitivity analysis to analyze the effects of a number of uncertain input parameters on the total cost.

3.1. Mathematical Optimization Framework. The mathematical optimization framework for structuring the fleet of a car-sharing company considering traffic congestion levels over a certain planning period is presented and discussed in this subsection. The formulation is adapted and expanded from the optimization framework in Feng and Figliozzi [37]; which was developed for the fleet composition of an urban freight transport company. Since the traffic congestion level is an important and effective factor in minimizing the total cost within the context of car-sharing services, the previously developed framework needs to be adapted to take such a factor into consideration.

These indices are used throughout the paper as follows:

(i) $K \in k = \{1, \cdots, K\}$ represents each type of vehicle technology
(ii) $i \in A = \{0, \cdots, A_k\}$ represents the age of a vehicle of type k
(iii) $t \in T = \{0, \cdots, T\}$ represents the year of the planning time period
(iv) $s \in S = \{1, \cdots, S\}$ refers to the level of traffic congestion in a day

The decision variables are as follows:

(i) $X_{i,t,k}$: number of age i type k vehicles used in year t
(ii) $Y_{i,t,k}$: number of age i, type k salvaged vehicles at the end of year t
(iii) $Z_{t,k}$: number of new type k purchased vehicles at the beginning of year t
(iv) $x_{i,t,k,s}$: total number of kilometers traveled by vehicles of type k age i during the level of s traffic congestion in year t

The parameters are denoted as follows:

(i) K: number of vehicle types
(ii) T: span of the planning period
(iii) S: level of traffic congestion of a typical day of operation

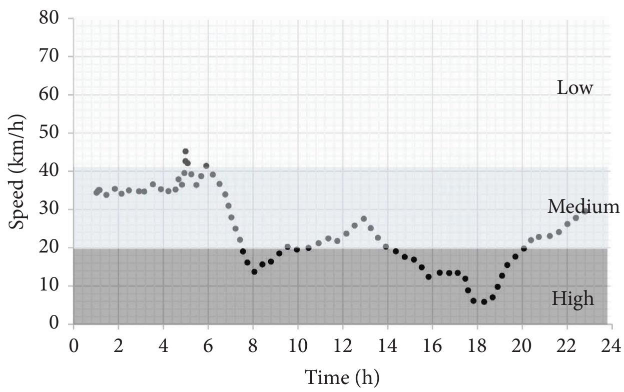

Figure 1: Levels of traffic congestion considering speed and different blocks of time.

(iv) A_k: maximum age of vehicle type k

(v) dr: discount rate for taking into account the devaluation of money with time

(vi) b_t: budget of year t

(vii) $w\ d$: working days in the year

(viii) $d_{t,s}$: demand related to the level of s traffic congestion in year t

(ix) $u_{i,t,k}$: the maximum distance that can be traveled by a vehicle of type k and age i in year t

(x) $v_{k,t}$: purchase cost (€) per unit of type k vehicle during period t

(xi) $s_{i,k}$: salvage revenue (€) of an age i, type k vehicle

(xii) $e_{i,t,k,s}$: per-km energy cost (€/km) of vehicle type k of age i during level s of traffic congestion of year t

(xiii) $m_{i,t,k,s}$: per-km operation and maintenance cost (€/km) of vehicle k of age i during level s of traffic congestion of year t

(xiv) $em_{i,k,s}$: CO_2 emission cost (€/km) of vehicles of age i and type k during level s of traffic congestion

3.1.1. Objective Function. The objective function minimizes the total cost. The total cost is composed of various cost elements, namely, energy, operation and maintenance, purchase, and emission costs. We actualized the costs at the beginning of the planning period. Since the objective function is linear and the decision variables take a nonnegative integer and real values, problem (1) is thus a mixed-integer linear programming problem. Therefore, to minimize the total cost, the following optimization problem is solved as follows:

$$
\begin{aligned}
\mathrm{Min}TC &= \sum_{t=0}^{T-1}\sum_{k=1}^{k} v_{k,t} z_{t,k}(1+dr)^{-t} - \sum_{i=1}^{A_k}\sum_{t=0}^{T}\sum_{k=1}^{K} s_{i,k} Y_{i,t,k}(1+dr)^{-t} \\
&\quad + \sum_{i=0}^{A_k-1}\sum_{t=0}^{T-1}\sum_{k=1}^{K}\sum_{s=1}^{S}\left(e_{i,t,k,s} + m_{i,t,k,s} + em_{i,k,s}\right) x_{i,t,k,s}(1+dr)^{-t}, \\
s.t \sum_{s=1}^{S} x_{i,t,k,s} &\le w\ d\, u_{i,t,k} X_{i,t,k} \quad \forall i \in A - \{A_k\}, \quad \forall k \in K, \quad \forall t \in T - \{T\}, \\
\sum_{k=1}^{K}\sum_{i=0}^{A_k-1} x_{i,t,k,s} &\ge d_{t,s} \quad \forall s \in S, \forall t \in T - \{T\}, \\
&\cdot \sum_{k=1}^{K} v_{k,t} z_{t,k} \quad \forall t \in \{0,1,2,\ldots,T-1\}, \\
X_{(i-1)(t-1),k} &= X_{i,t,k} + Y_{i,t,k} \quad \forall t \in T, \forall k \in K, \forall i \in A - \{0\}, \\
Z_{t,k} &= X_{0,t,k} \quad \forall t \in T, \forall k \in K, \\
X_{i,T,k} &= 0 \quad \forall k \in K, \forall i \in A - \{0, A_k\}, \\
X_{A_k,t,k} &= 0 \quad \forall t \in T, \forall k \in K, \\
Y_{0,t,k} &= 0 \quad \forall t \in T, \forall k \in K, \\
&\cdot Z_{t,k}, X_{i,t,k}, Y_{i,t,k} \in Z^+ = \{0,1,2,\ldots\},
\end{aligned}
\tag{1}
$$

$x_{i,tk,s} \in R^+$, where R^+ represents the set of nonnegative real numbers.

The total cost (€) associated with the car-sharing service business over the planning period consisted of the following components:

Purchase cost:

$$PC = \sum_{t=0}^{T-1}\sum_{k=1}^{K} v_{k,t} Z_{t,k}(1+\mathrm{d}r)^{-t}. \tag{2}$$

Salvage revenue:

$$SR = \sum_{i=1}^{A_k}\sum_{t=0}^{T}\sum_{k=1}^{K} s_{i,k}Y_{i,t,k}\,(1+\mathrm{d}r)^{-t}. \quad (3)$$

Energy cost:

$$EC = \sum_{i=0}^{A_k-1}\sum_{t=0}^{T-1}\sum_{k=1}^{K}\sum_{s=1}^{S} e_{i,t,k,s}x_{i,t,k,s}\,(1+\mathrm{d}r)^{-t}. \quad (4)$$

Operation and maintenance cost:

$$OP\,\&\,MC = \sum_{i=0}^{A_k-1}\sum_{t=0}^{T-1}\sum_{k=1}^{K}\sum_{s=1}^{S} m_{i,t,k,s}x_{i,t,k,s}\,(1+\mathrm{d}r)^{-t}. \quad (5)$$

Emission cost:

$$EmC = \sum_{i=0}^{A_k-1}\sum_{t=0}^{T-1}\sum_{k=1}^{K}\sum_{s=1}^{S} em_{i,k,s}x_{i,t,k,s}\,(1+\mathrm{d}r)^{-t}. \quad (6)$$

Constraint (2) concerns the total distance (in kilometers) traveled in any year, which cannot be greater than the maximum distance traveled by all types of vehicles used. In addition, in constraint (3), the distance traveled by all vehicles of any type and age for each demand level in any year must be greater than the demand for the corresponding level of s traffic congestion in that year. Constraint (4) shows that the company has a yearly limited budget for purchasing new vehicles. Constraint (5) enforces that in any year of the planning period, the number of vehicles used and salvaged of any type must be equal to the number of vehicles used of the same type in the preceding year. Constraint (6) ensures that in any planning period year, the new vehicles of any type introduced into the fleet must be the same as the number of purchased vehicles of that type. Constraint (7) forces all remaining vehicles to be sold at the end of the planning time period. Constraint (8) ensures that when a vehicle reaches its maximum age, it must be salvaged. Constraint (9) ensures that new vehicles cannot be salvaged immediately. Lastly, in constraint (10), decision variables $Z_{t,k}$, $X_{i,t,k}$ and $Y_{i,t,k}$ can take only non-negative integer values, and $x_{i,t,k,s}$ can also take nonnegative real values.

4. Data and Assumptions

For the numerical experiments, we assume that a car-sharing company has the goal of deriving an optimal combination of its fleet from two available types of diesel and electric vehicles both with the same passenger capacity. These two types are denoted as $k = 1$ and $k = 2$ for DVs and EVs, respectively. Tax incentives for diesel (https://taxfoundation.org/gas-taxes-europe-2019/) cars, better fuel economy in most European countries, and lower tailpipe emissions of CO_2 for diesel (https://autotraveler.ru/en/spravka/fuel-price-in-europe.html) [45] compared to gasoline are the main reasons for choosing this type of ICEV in our numerical experiments. The data regarding the two types of vehicles and other input parameters are given in Table 1.

With regard to the lifetime of vehicles, considering the European Automobile Manufacturers Association (https://www.aut.fi/en/frontpage_vanha/statistics/international_statistics/average_age_of_passenger_cars_in_some_european_countries), which has reported an age of 8 years for passenger cars in some European countries, and following Mahut et al. [46]; we consider a lifetime of 8 years for both passengers DVs and EVs. In addition, a discount rate of 5% [47] is used. By considering the foreseen daily utilization and EV battery lifetime of 160,000 km [48, 49], each EV will need two batteries over its eight-year operational lifetime. We include the discounted cost of the extra battery in the EV purchase price.

For the range limitation of EVs, the Nissan Leaf, the electric car model that registered the highest number of sales in Europe in 2018 and the third leading passenger electric vehicle in 2020 (https://www.statista.com/statistics/965507/eu-leading-passenger-electric-vehicle-models/), was the EV analyzed in this study. The Leaf has a range of 264 kilometers with one full charge of battery. (https://www.nissanusa.com/vehicles/electric-cars/leaf/features/range-charging-battery.html).

To calculate the salvage or resale value, we use the following formula proposed by Feng and Figliozzi [37]:

$$s_{i,k} = (1-\theta_k)s_{(i-1)k} = v_k(1-\theta_k)^i, \quad \forall k \in K, \forall i \in A-\{1\}, \quad (7)$$

where θ_k is the rate at which vehicle type k is depreciated. Based on the values reported by Messagie et al. [50], we set depreciation rates per year of 17% and 28% for DVs and EVs, respectively.

For the medium TCL, we use an energy consumption of 0.062 lit/km [51] and 0.145 kWh/km [52] for DVs and EVs, respectively.

Based on the data given in Table 2, the energy costs per kilometer are calculated using the formulas presented in the following equations:

$$e_{i,t,s,1} = R_{s,1}\left(\frac{\mathrm{lit}}{\mathrm{km}}\right)\times G_{dv}\times e^{\widehat{f}_1\cdot t} \quad \forall i \in A\,\forall t \in T\,\forall s \in S=\{1,2,3\}, \quad (8)$$

$$e_{i,t,s,2} = Q_{s,2}\left(\frac{kWh}{km}\right)\times H_{ev}\times e^{\widehat{f}_2\cdot t} \quad \forall i \in A-\{1\}\,\forall t \in T\,\forall s \in S=\{1,2,3\}, \quad (9)$$

Table 1: Input-parameter data.

Vehicle type	DVs	EVs
Lifetime (years)	$A_1 = 8$	$A_2 = 8$
Discount rate (%)	0.05	0.05
Annual use (km)	40000	40000
Daily use (km)	160	160
Planning time horizon (years)	16	16
Depreciation rate (%)	0.17	0.28
Energy cost growth rate (Pordata 2018) (%)	0.0582	0.0289
Purchase cost (Nissan, 2020) (€)	14000	28000
Energy consumption in low TCL (s_1)	0.0465 lit/km	0.1087 kWh/km
Energy consumption in medium TCL (s_2)	0.062 lit/km	0.145 kWh/km
Energy consumption in peak TCL (s_3)	0.0775 lit/km	0.1812 kWh/km
Energy cost (Pordata 2018)	1.16 €/lit	0.16 €/kWh
CO_2 emissions (well-to-wheel)	2.63 kg/lit	0.47 kg/kWh

Table 2: Summary of characteristics of previous studies.

References	Method	Model	Context	Fleet size	Vehicle replacement/ composition problem	TCL
[26]	Opt	Mixed-integer linear programming (MILP)	Car-sharing system	✓	—	—
[27]	Opt	(MILP)	Car-sharing system	✓	—	—
[28]	Opt	Integer linear programming (ILP)	Car-sharing system	✓	✓	—
[29]	Opt	Stochastic mixed-integer program (SMIP)	Fleet management shared-vehicle system	✓	—	—
[32]	Opt	(ILP)	Car-sharing system electric mobility	✓	✓	—
[34]	Survey	Total cost of ownership model	Electric mobility	—	—	—
[31]	Opt	Mixed integer program (MIP)	Shared mobility	✓	—	—
[35]	Opt	(MILP)	Car-sharing system electric mobility	✓	—	—
[36]	Opt	Simulation model	EV- sharing system	✓	—	—
[37]	Opt	(MIP)	Urban freight fleet replacement problem	✓	✓	—
[38]	Opt	(MIP)	Urban freight fleet replacement and composition problem	✓	✓	—
[39]	Opt	Mixed integer quadratic programming (MIQP)	Urban freight fleet replacement problem	✓	✓	—
This research	Opt	(MILP)	Car-sharing system	✓	✓	✓

where $R_{s,1}$ and $Q_{s,2}$ represent the energy consumption per km. G_{dv} and H_{ev} are the corresponding parameters for the energy cost of DVs and EVs as presented in Table 1, and $\widehat{f}_1$ and f_2 are the annual growth rates of 5.82% and 2.89% [39] for diesel and electricity prices, respectively. The price growth rates were defined on the basis of the annual diesel price history from 1980 to 2014 and the electricity price history from 1991 to 2014 in Portugal (https://www.pordata.pt/Portugal).

We should mention that we made the right-hand side of (8) and (9) independent of the age of vehicles (i.e., i). In fact, due to a lack of data regarding the energy consumption of vehicles with age, similar to Feng and Figliozzi [37] and Ahani et al. [39]; we assumed that $R_{s,1}$ and $Q_{s,2}$ are fixed values for each i.

On average, well-to-wheel CO_2 emissions by DV and EV are approximately 2.63 kg/lit and 0.47 kg/kWh, respectively [53]. The CO_2 emission value for EVs is calculated by taking into account the emissions produced by different types of power generation technologies. Therefore, the following equations give the emission cost of each type of vehicle based on its age:

$$\begin{aligned} em_{i,s,1} &= 0.00263\left(\frac{\tan}{\text{lit}}\right) \times R_{s,1}\left(\frac{\text{lit}}{\text{km}}\right) \times ec, \quad \forall i \in A - \{A_k\}, \\ em_{i,s,2} &= 0.47\left(\frac{\text{kg}}{\text{kWh}}\right) \times Q_{s,2}\left(\frac{\text{kWh}}{\text{km}}\right) \times 0.001\left(\frac{\text{ton}}{\text{kg}}\right) ec, \quad \forall i \in A - \{A_k\}. \end{aligned} \tag{10}$$

An *ec* value of €25/ton is considered [54].

Following the maintenance cost data analysis from Carstens [55], each car has a cost of approximately 0.04 euro/km. The mileage and age of a vehicle affect its maintenance cost. The total maintenance cost for EVs is at most 60% of the maintenance cost for ICEVs [50]. Hence, we use the following quadratic functions extrapolated from the data adopted from Carstens [55] to estimate the maintenance costs of ICEVs and then use them to approximate the maintenance costs of EVs.

$$m_{i,1} = -0.0015i^{\wedge}2 - 0.011i + 0.076, \quad \forall i \in A - \{0\},$$
$$m_{i,2} = 0.6\left(-0.0015i^{\wedge}2 - 0.011i + 0.076\right), \quad \forall i \in A - \{0\}. \tag{11}$$

Regarding other input parameters, the following are assumed:

(i) The company has 20 diesel vehicles of different ages in its initial fleet. 12 vehicles of ages 0–3 years with three vehicles of each age and 8 vehicles of ages 4–7 years with two vehicles of each age.

(ii) There are three traffic congestion levels (TCLs): low (s1), medium (s2), and high (s3) with vehicle demands of 20%, 30%, and 50% of the total demand, respectively (i.e., $d_{t,1} = 0.2d_t, d_{t,2} = 0.3d_t, an\ d\ d_{t,3} = 0.5d_t$).

(iii) We assume that both DVs and EVs are used 160 km per day, which is equivalent to 40,000 km per year based on a total of 250 working days in a year.

(iv) An annual budget of 56,000 euros is assumed for purchasing new vehicles.

(v) We assume that the energy consumption of DVs in the low and high TCLs is 25% less and 25% more than that of the medium TCL, respectively.

(vi) We also assumed a scenario without incorporating TCL into the model. For this scenario, we consider the energy consumption of 0.062 lit/km and 0.145 kWh/km for DVs and EVs, respectively.

(vii) During each year, the total demand for car-sharing vehicles is supposed to be equivalent to the total distance traveled by all 20 vehicles in the corresponding year ($d_t = 40,000km \times 20$).

(viii) We assumed that $R_{s,1}$ and $Q_{s,2}$ are independent of age.

5. Results and Discussion

This section presents the results of resolving the mixed-integer linear optimization problem (1) (see Table 3) using the CPLEX solver of GAMS version 27.3 [56] on a laptop computer with CPU Intel core i3–4030U 1.90 GHz and RAM memory of 4 GB running Windows 10 64 bits. We present the total number of purchased vehicles, total distance traveled in each traffic congestion level by each type of vehicle, number of vehicles used, and number of salvaged vehicles in each year of the planning period. An elasticity analysis is also performed to show the magnitude of the effects of certain input parameters on the total cost.

Table 3: Model statistics.

Name	Number
Constraints	745
Variables	1565
Discrete variables	646
Execution time	0.06 seconds

Figure 2 shows the number of vehicles used each year for the two types of vehicles. Regarding the number of vehicles used, the share of electric vehicles in the fleet increases over time up to year 12 of the planning period and then remains constant until year 14 and then begins to decrease. Keeping in mind that the initial fleet has been composed of only DVs, the reason for the increase in the share of EVs and replacing DVs in the fleet is their low operating costs, especially when considering the traffic congestion level, which is a major factor affecting the fuel consumption of a vehicle. We can see that the share of EVs in the fleet begins to decrease after year 14 of the planning period, and the main reasons are their high purchase price and high depreciation rate. Indeed, these two factors mean that EVs, when compared with DVs, are not competitive for just the last two years of the planning time period. Had the planning period been infinite, then the share of EVs would have increased constantly over the course of the said planning period. Additionally, Figure 3 shows the number of purchased DVs and EVs over the 16 years of the planning period. The number of EVs decreases toward the end of the planning period because the depreciation rate for EVs is higher than that of DVs. Figure 4 shows the number of vehicles salvaged at the end of each year and at the end of the planning time period when all vehicles are salvaged due to the end of the operation.

For a more thorough analysis, we present in Figures 5 and 6 the total traveled distance for each type of vehicle and the traffic congestion level. As stated previously, we assume that the initial fleet of the car-sharing service company is made up of DVs only. The figures show that for a high TCL ($s = 3$), the total distance traveled by EVs begins to increase year by year, and from year eight until year fourteen of the planning period, the total traveled distance in this TCL is covered only by EVs. In the case of medium TCL ($s = 2$), albeit in comparison to high TCL with a slower increase in the share of EVs, and only from year 9 to year 13 of the planning period is the entire demand in this TCL met by EVs. DVs remain competitive chiefly for low TCL ($s = 1$), as the operational cost for this TCL is lower than those of the other two levels. As previously mentioned, the increase in the share of traveled distance by DVs for the high and medium TCLs toward the end of the planning period can be attributed to the high purchase price and the high depreciation rate of EVs, which render them less economically viable for just a few years of use in the fleet.

We also assumed a scenario without incorporating the traffic congestion level into the model to show that the traffic congestion level has an important impact on the total cost.

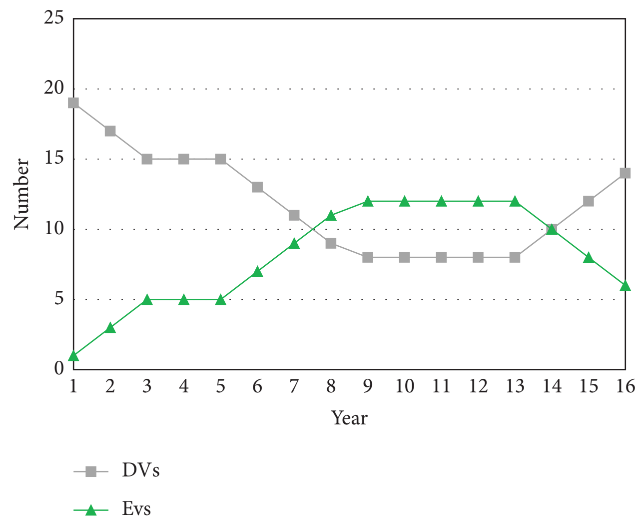

Figure 2: Number of vehicles used during the planning period.

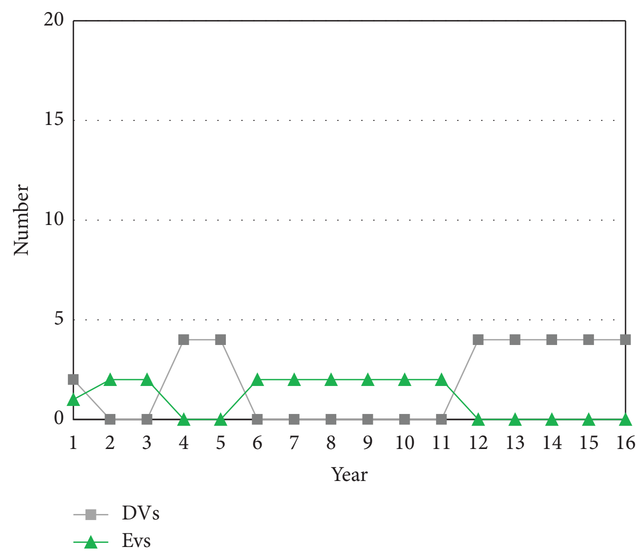

Figure 3: Number of purchased vehicles during the planning period.

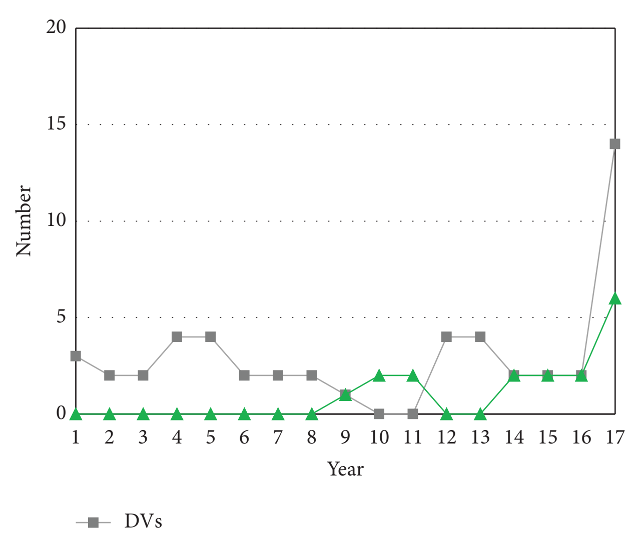

Figure 4: Number of salvaged vehicles during the planning period.

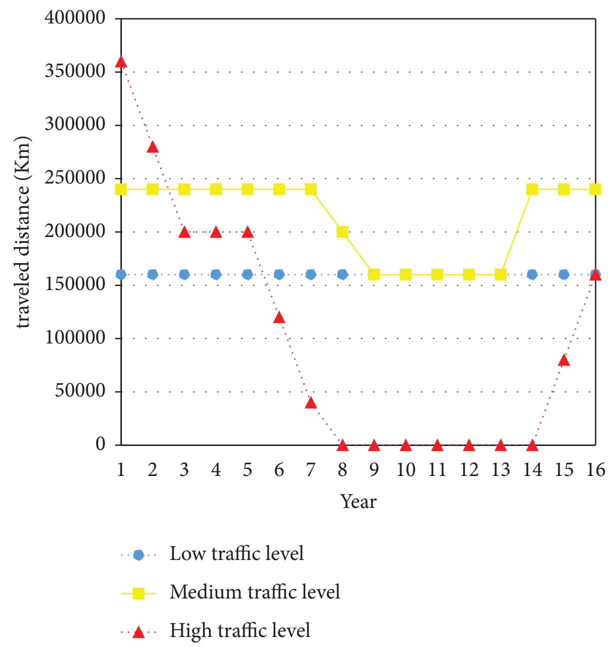

Figure 5: Traveled distance of diesel vehicles for different levels of traffic congestion.

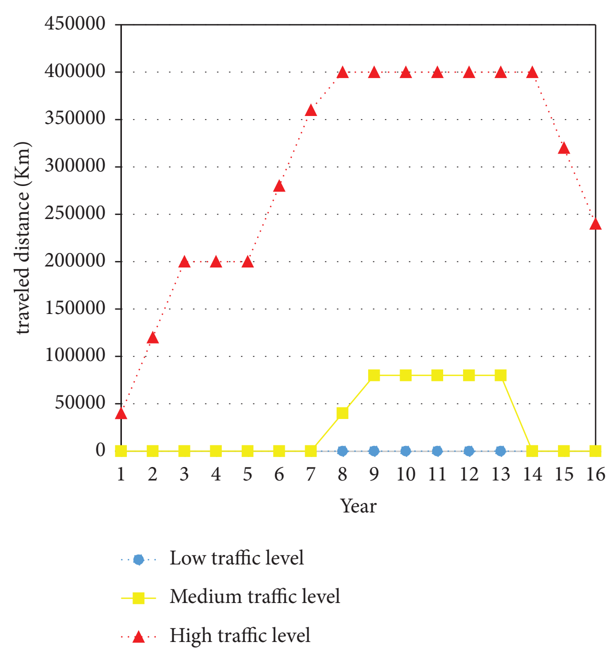

Figure 6: Traveled distance of electric vehicles for different levels of traffic congestion.

As we mentioned previously for this scenario, we consider the energy consumption of 0.062 lit/km and 0.145 kWh/km for DVs and EVs, respectively. This scenario led to an increase of 18% (from 1,955,629.032 to 2,310,844.077) in the total cost.

Table 4: Per-km discounted elasticity analysis of total cost for different factors.

Factor (range of values) (unit)	Baseline value	EA (TC, p)
Depreciation rate EVs (17–27) (%)	22%	0.012
Depreciation rate EVs (23–33) (%)	28%	0.053
Depreciation rate EVs (29–39) (%)	34%	0.068
DVs growth rate energy price (2.91–8.73) (%)	5.82%	0.256
EVs growth rate energy price (1.44–4.33) (%)	2.89%	0.018
Discount rate (3–7) (%)	5%	−0.180
EVs purchase price (25200–30800) (€)	28000 €	0.398
Energy price (1.044–1.275) (€/lit)	1.16 €/lit	0.351
Energy price (0.144–0.176) (€/kWh)	0.16 €/kWh	0.072
Emission cost (22.5–27.5) (€/ton)	25 €/ton	0.023
Lifetime (6–10) years	8 years	0.025
EVs maintenance cost (0.024–0.028) (€/km)	0.0260 €/km	0.037

5.1. Elasticity Analysis. As mentioned previously, there is a degree of uncertainty associated with some of the input parameters. Variations in these parameters can also impact the total cost. We performed an elasticity analysis on a number of key parameters to test their impacts on the total cost. To this end, we used the arc elasticity formula [57]as follows:

$$EA(TC,p) = \frac{\%chance\ in\ total\ \text{cost}}{\%change\ in\ parameter\ p} = \frac{\{p1+p2\}}{\{TC1+TC2\}} \times \frac{\{TC2-TC1\}}{\{P2-p1\}}, \tag{12}$$

where EA (TC, p) represents the discounted total cost (TC) per km in response to a change in parameter *p*.

Elasticity analysis was performed for different ranges of values to assist the operator in determining which parameter has the main impact on its optimal vehicle replacement decision. Regarding the deprecation rate of EVs, an elasticity analysis was performed for three different intervals. As expected, the purchase price of EVs, the energy prices related to the operation of DVs, and the growth rate in diesel prices have the highest impact on the total cost. The results of the elasticity analysis are presented in Table 4. A 1% change in one of these parameters leads to increases of 0.40%, 0.35%, and 0.26% in the total cost, respectively. For the discount rate range, the elasticity is negative, which means that when the discount rate increases by 1%, the total cost decreases by 0.18%.

6. Conclusions

Car-sharing can help resolve traffic congestion and emission issues arising from increasing mobility within urban areas. In comparison to diesel vehicles, EVs perform better in regard to energy consumption during peak-hour traffic congestion and low-speed flows. Taking this crucial factor into consideration, an optimization framework for introducing new vehicles of different types into the fleet of a car-sharing company over a certain planning period was presented. The developed framework considers the energy consumption and emissions of different types of vehicles at different levels of traffic congestion. To the best of our knowledge, this is the first time that such a framework has been presented for the optimal composition of the fleet of a car-sharing service. The numerical results showed that EVs, compared to DVs, become more competitive year after year during the planning period. The reason for the increase in the share of EVs is their low operating costs. More important, their competitiveness increases with the intensity of traffic congestion. Therefore, any decision made by a car-sharing operator that ignores traffic congestion intensity throughout the day as a factor would result in an onus, in the form of extra costs, for the company in question.

In this paper, an elasticity analysis is done to consider the uncertainty of input parameters such as the energy cost, maintenance cost, EV purchase price, and emission cost of different types of vehicles. In future work, it will be worthwhile to analyze the effect of these uncertainty parameters by using a portfolio theory approach such as the one developed by Ahani et al. [39]. We also assumed that the range limitation of EVs was not a determining factor for the purchase decision. Depending on the demand level for car-sharing services, there are some situations in which such an assumption seems unrealistic. Hence, another line of research could involve developing a vehicle replacement and assignment optimization framework by considering the range restriction of EVs and uncertainties associated with the network of available charging stations and demand for car-sharing service across an urban area. In this work, we did not take into account the charging station location, and no limitation was assumed with regard to the demand for charging EVs in a network of charging stations. However, in real scenarios, the network of charging stations might have a limited capacity for satisfying the uncertain demands for recharging the EVs. There are various research studies on finding optimal locations for refueling stations under different scenarios and conditions [58–64]. Therefore, from the standpoint of an urban decision-maker, the integration of the frameworks developed in the aforementioned studies into the optimization framework of the current research study will be another interesting future line of research.

Data Availability

The data used to support the findings of this study are included within the article.

Conflicts of Interest

The authors declare that they have no conflicts of interest.

Acknowledgments

The authors would like to acknowledge the Foundation for Science and Technology for the financial support with references (UIDB/04625/2020) and (SFRH/BD/89258/2012). The authors would also like to acknowledge funding from the project Horizon 2020 "ASSURED–UAM, Acceptance, Safety, and Sustainability Recommendations for Efficient Deployment of UAM" and the project "C-Tech–Climate Driven Technologies for Low Carbon Cities" of the MIT-Portugal Program.

References

[1] R. Katzev, "Car sharing: a new approach to urban transportation problems," *Analyses of Social Issues and Public Policy*, vol. 3, no. 1, pp. 65–86, 2003.

[2] S. Lee, "A review of carsharing research: with a focus on domestic thesis and research papers," *Inst. Korean Reg. Stud.*vol. 62, pp. 3–17, 2015.

[3] S. A. Shaheen, N. D. Chan, A. Bansal, and A. P. Cohen, *Shared Mobility: Definitions, Industry Developments, and Early Understanding*, Transportation Sustainability Research Center, Berkeley, CA, USA, 2015, http://innovativemobility.org/wp.

[4] J. Jung and Y. Koo, "Analyzing the effects of car sharing services on the reduction of greenhouse gas (GHG) emissions," *Sustainability*, vol. 10, no. 2, p. 539, 2018.

[5] Y. Hui, Y. Wang, Q. Sun, and L. Tang, "The impact of carsharing on the willingness to postpone a car purchase: a case study in Hangzhou, China," *Journal of Advanced Transportation*, vol. 2019, Article ID 9348496, 11 pages, 2019.

[6] A. Millard-Ball, "Car-sharing: where and how it succeeds," vol. 60, Transportation Research Board, Washington, D.C, USA, 2005, TCRP Report 108.

[7] G. Cooper, D. A. Howe, and P. Mye, *The Missing Link: An Evaluation of Carsharing*, Portland Inc, Portland, Oregon, 2000.

[8] B. Yu, Y. Ma, M. Xue et al., "Environmental benefits from ridesharing: a case of Beijing," *Applied Energy*, vol. 191, pp. 141–152, 2017.

[9] H. Nijland and J. van Meerkerk, "Mobility and environmental impacts of car sharing in The Netherlands," *Environmental Innovation and Societal Transitions*, vol. 23, pp. 84–91, 2017.

[10] E. Martin, S. A. Shaheen, and J. Lidicker, "Impact of carsharing on household vehicle holdings: results from North American shared-use vehicle survey. Transportation Research Record," *Journal of the Transportation Research Board*, vol. 2143, pp. 151–158, 2010.

[11] E. W. Martin and S. A. Shaheen, "Greenhouse gas emission impacts of carsharing in North America," *IEEE Transactions on Intelligent Transportation Systems*, vol. 12, no. 4, pp. 1074–1086, 2011.

[12] L. Hu and Y. Liu, "Joint design of parking capacities and fleet size for one-way station-based carsharing systems with road congestion constraints," *Transportation Research Part B: Methodological*, vol. 93, pp. 268–299, 2016.

[13] S. A. Shaheen, N. D. Chan, and E. Farrar, "Carsharing's impact and future," in *Book: The Sharing Economy and the Relevance for Transport*, pp. 87–120, Elsevier, Amsterdam, Netherlands, 2019.

[14] T. D. Chen and K. M. Kockelman, "Carsharing's life-cycle impacts on energy use and greenhouse gas emissions," *Transportation Research Part D: Transport and Environment*, vol. 47, pp. 276–284, 2016.

[15] V. Roblek, M. Meško, and I. Podbregar, "Impact of car sharing on urban sustainability," *Sustainability*, vol. 13, no. 2, p. 905, 2021.

[16] M. Balac, H. Becker, F. Ciari, and K. W. Axhausen, "Modeling competing free-floating carsharing operators–A case study for Zurich, Switzerland," *Transportation Research Part C: Emerging Technologies*, vol. 98, pp. 101–117, 2019.

[17] D. Fiedler, M. Čáp, and M. Čertický, "Impact of mobility-on demand on traffic congestion: simulation-based study," in *Proceedings of the 2017 IEEE 20th International Conference on Intelligent Transportation Systems (ITSC)*, pp. 1–6, IEEE, Yokohama, Japan, October 2017.

[18] F. Ciari, B. Bock, and M. Balmer, "Modeling station-based and free-floating carsharing demand: test case study for berlin," *Transportation Research Record Journal of the Transportation Research Board*, vol. 2416, no. 1, 2014.

[19] A. P. Cohen, S. A. Shaheen, and R. McKenzie, "Carsharing: a guide for local planners," *Journal of Planning Advisory Service Memo*, vol. 1040, 2008, http://escholarship.org/uc/item/4kf3x31h,%20UCD-ITS-RP-08-16.

[20] S. A. Shaheen and A. P. Cohen, "Carsharing and personal vehicle services: worldwide market developments and emerging trends," *International Journal of Sustainable Transportation*, vol. 7, no. 1, pp. 5–34, 2012.

[21] X. Li, J. Ma, J. Cui, A. Ghiasi, and F. Zhou, "Design framework of large-scale one-way electric vehicle sharing systems: a continuum approximation model," *Transportation Research Part B: Methodological*, vol. 88, pp. 21–45, 2016.

[22] S. Frost, "Strategic insight of the global carsharing market," Technical Reports Series 90-18, Frost & Sullivan, San Antonio, TX, USA, 2014.

[23] C. King, W. Griggs, F. Wirth, and R. Shorten, "Using a car sharing model to alleviate electric vehicle range anxiety," in *Proceedings of the 16th Yale Workshop on Adaptive and Learning Systems*, pp. 130–135, New Haven, CT, USA, June 2013.

[24] S. Mamarikas, S. Doulgeris, Z. Samaras, and L. Ntziachristos, "Traffic impacts on energy consumption of electric and conventional vehicles," *Transportation Research Part D: Transport and Environment*, vol. 105, Article ID 103231, 2022.

[25] B. Nykvist, F. Sprei, and M. Nilsson, "Assessing the progress toward lower priced long range battery electric vehicles," *Energy Policy*, vol. 124, pp. 144–155, 2019.

[26] C. M. Monteiro, C. A. S. Machado, M. d. O. Lage, F. T. Berssaneti, C. A. Davis, and J. A. Quintanilha, "Optimization of carsharing fleet size to maximize the number of clients served," *Computers, Environment and Urban Systems*, vol. 87, Article ID 101623, 2021.

[27] P. Ströhle, C. M. Flath, and J. Gärttner, "Leveraging customer flexibility for car-sharing fleet optimization," *Transportation Science*, vol. 53, no. 1, pp. 42–61, 2019.

[28] A. Wallar, J. Alonso-Mora, and D. Rus, "Optimizing vehicle distributions and fleet sizes for shared mobility-on-demand," in *Proceedings of the 2019 International Conference on Robotics and Automation (ICRA)*, pp. 3853–3859, IEEE, Montreal, Canada, May 2019.

[29] R. Nair and E. Miller-Hooks, "Fleet management for vehicle sharing operations," *Transportation Science*, vol. 45, no. 4, pp. 524–540, 2011.

[30] J. Li, Y. S. Chen, H. Li, I. Andreasson, and H. V. Zuylen, "Optimizing the fleet size of a personal rapid transit system: a case study in port of rotterdam," in *Proceedings of the 13th International IEEE Conference on Intelligent Transportation Systems (ITSC)*, pp. 301–305, IEEE, Funchal, Portugal, September 2010.

[31] H. Hosni, J. Naoum-Sawaya, and H. Artail, "The shared-taxi problem: formulation and solution methods," *Transportation Research Part B: Methodological*, vol. 70, pp. 303–318, 2014.

[32] R. F. Lemme, E. F. Arruda, and L. Bahiense, "Optimization model to assess electric vehicles as an alternative for fleet composition in station-based car sharing systems," *Transportation Research Part D: Transport and Environment*, vol. 67, pp. 173–196, 2019.

[33] G. Brandstätter, M. Kahr, and M. Leitner, "Determining optimal locations for charging stations of electric car sharing systems under stochastic demand," *Transportation Research Part B: Methodological*, vol. 104, pp. 17–35, 2017.

[34] S. Bubeck, J. Tomaschek, and U. Fahl, "Perspectives of electric mobility: total cost of ownership of electric vehicles in Germany," *Transport Policy*, vol. 50, pp. 63–77, 2016.

[35] S. Weikl and K. Bogenberger, "A practice-ready relocation model for free-floating carsharing systems with electric vehicles – mesoscopic approach and field trial results," *Transportation Research Part C: Emerging Technologies*, vol. 57, pp. 206–223, 2015.

[36] S. Nakayama, T. Yamamoto, and R. Kitamura, "Simulation analysis for the management of an electric vehicle-sharing system: case of the kyoto public-car system," *Transportation Research Record Journal of the Transportation Research Board*, vol. 1791, no. 1, pp. 99–104, 2002.

[37] W. Feng and M. Figliozzi, "An economic and technological analysis of the key factors affecting the competitiveness of electric commercial vehicles: a case study from the USA market," *Transportation Research Part C: Emerging Technologies*, vol. 26, pp. 135–145, 2013.

[38] O. Jabali and G. Erdoğan, *Continuous Approximation Models for the Fleet Replacement and Composition Problem (No. CIRRELT-2015-64)*, CIRRELT, Montreal, Canada, 2015.

[39] P. Ahani, A. Arantes, and S. Melo, "A portfolio approach for optimal fleet replacement toward sustainable urban freight transportation," *Transportation Research Part D: Transport and Environment*, vol. 48, pp. 357–368, 2016.

[40] Y. M. He, J. Kang, Y. L. Pei, B. Ran, and Y. T. Song, "Study on a prediction model of superhighway fuel consumption based on the test of easy car platform," *Sustainability*, vol. 12, no. 15, p. 6260, 2020.

[41] F. Grée, V. Laznikova, B. Kim, G. Garcia, T. Kigezi, and B. Gao, "Cloud-based big data platform for vehicle-to-grid (v2g)," *World Electric Vehicle Journal*, vol. 11, no. 2, p. 30, 2020.

[42] Y. H. Huang and J. H. Wu, "A portfolio risk analysis on electricity supply planning," *Energy Policy*, vol. 36, no. 2, pp. 627–641, 2008.

[43] J.-H. Wu and Y.-H. Huang, "Electricity portfolio planning model incorporating renewable energy characteristics," *Applied Energy*, vol. 119, pp. 278–287, 2014.

[44] Y. Ji, J. Luo, and N. Geroliminis, "Empirical observations of congestion propagation and dynamic partitioning with probe data for large-scale systems," *Transportation Research Record Journal of the Transportation Research Board*, vol. 2422, no. 1, pp. 1–11, 2014.

[45] D. Magueta, M. Madaleno, M. Ferreira Dias, and M. Meireles, "New cars and emissions: effects of policies, macroeconomic impacts and cities characteristics in Portugal," *Journal of Cleaner Production*, vol. 181, pp. 178–191, 2018.

[46] F. Mahut, J. Daaboul, M. Bricogne, and B. Eynard, "Product-Service Systems for Servitization of the automotive industry: a literature review," *International Journal of Production Research*, vol. 55, no. 7, pp. 2102–2120, 2017.

[47] P. Baptista, S. Melo, and C. Rolim, "Energy, environmental and mobility impacts of car sharing systems. Empirical results from Lisbon, Portugal," *Procedia-Social and Behavioral Sciences*, vol. 111, pp. 28–37, 2014.

[48] G. Palmer and J. Floyd, "Chapter of Energy Primer for Storage Analysis in," *Book: Energy Storage and Civilization*, Springer, Cham, Switzerland, pp. 41–56, 2020.

[49] A. Ajanovic and R. Haas, "Electric vehicles: solution or new problem?" *Environment, Development and Sustainability*, vol. 20, no. S1, pp. 7–22, 2018.

[50] M. Messagie, K. Lebeau, T. Coosemans, C. Macharis, and J. van Mierlo, "Environmental and financial evaluation of passenger vehicle technologies in Belgium," *Sustainability*, vol. 5, no. 12, pp. 5020–5033, 2013.

[51] D. Lois, Y. Wang, A. Boggio-Marzet, and A. Monzon, "Multivariate analysis of fuel consumption related to eco-driving: interaction of driving patterns and external factors," *Transportation Research Part D: Transport and Environment*, vol. 72, pp. 232–242, 2019.

[52] J. Zhang, Z. Wang, P. Liu, D. Cui, and X. Li, "Analysis on influence factors of energy consumption of electric vehicles based on real-world driving data," in *Proceedings of the 11th International Conference on Applied Energy 2019, (ICAE2019)*, pp. 12–15, västerås, Sweden, January 2019.

[53] I. Adeniran, *The Impacts of Sustainable Concepts in Urban Freight Distribution-A Courier, Express and Parcel Case Study*, Doctoral dissertation, Technische Universität München, Munich, Germany, 2020.

[54] R. Gerlagh, R. J. R. K. Heijmans, and K. E. Rosendahl, "COVID-19 tests the market stability reserve," *Environmental and Resource Economics*, vol. 76, no. 4, pp. 855–865, 2020.

[55] S. Carstens, "Increasing the competitiveness of maintenance contract rates by using an alternative methodology for the calculation of average vehicle maintenance costs," *Journal of Transport and supply chain Management*, vol. 2, no. 1, pp. 1–11, 2008.

[56] Gams, *General Algebraic Modeling System (GAMS)*, GAMS Development Corporation, Washington, DC, USA, 2019.

[57] R. G. D. Allen, "The concept of arc elasticity of demand: I," *The Review of Economic Studies*, vol. 1, no. 3, pp. 226–229, 1934.

[58] M. Miralinaghi, G. H. de Almeida Correia, S. E. Seilabi, and S. Labi, "Designing a network of electric charging stations to mitigate vehicle emissions," in *2020 Forum on Integrated and Sustainable Transportation Systems (FISTS)*, pp. 95–100,

Institute of Electrical and Electronics Engineers (IEEE), Delft, Netherlands, 2020.

[59] M. Miralinaghi, Y. Lou, B. B. Keskin, A. Zarrinmehr, and R. Shabanpour, "Refueling station location problem with traffic deviation considering route choice and demand uncertainty," *International Journal of Hydrogen Energy*, vol. 42, no. 5, pp. 3335–3351, 2017.

[60] M. Miralinaghi, B. B. Keskin, Y. Lou, and A. M. Roshandeh, "Capacitated refueling station location problem with traffic deviations over multiple time periods," *Networks and Spatial Economics*, vol. 17, 2017.

[61] M. Ghamami, A. Zockaie, and Y. Nie, "A General Corridor Model for Designing Plug-In Electric Vehicle Charging Infrastructure to Support Intercity Travel," *Transportation Research Part C: Emerging Technologies*, vol. 68, 2016.

[62] Z.-H. Zhu, Z.-Y. Gao, J.-F. Zheng, and H.-M. Du, "Charging station location problem of plug-in electric vehicles," *Journal of Transport Geography*, vol. 52, pp. 11–22, 2016.

[63] R. R. Desai, E. Hittinger, and E. Williams, "Interaction of consumer heterogeneity and technological progress in the US electric vehicle market," *Energies*, vol. 15, no. 13, p. 4722, 2022.

[64] H. Zheng, X. He, Y. Li, and S. Peeta, "Traffic equilibrium and charging facility locations for electric vehicles," *Networks and Spatial Economics*, vol. 17, no. 2, pp. 435–457, 2016.